[0017] In candidate malignant lesion detection stage **120**, a machine learning based detection model **104** outputs detections **106** of malignant lesions in the form of a heat map from input mpMRI images **102** of a patient. Since the malignant lesions in detections **106** may be false positive detections of malignant lesions, the malignant lesions in detections **106** are considered candidate malignant lesions. In order to reduce the false positive detections of malignant lesions, false positive reduction stage **122** is applied. In false positive reduction stage **122**, the malignant lesions in detections **106** are identified as candidate malignant lesions by candidates generation module **108**, patches **110** associated with the candidate malignant lesions are extracted from mpMRI images **102**, and a machine learning based false positive (FP) reduction model **112** classifies the candidate malignant lesions as being true positive detections of a malignant lesion or false positive detections of a malignant lesion from patches **110** and outputs results of the classification as detections **114** of malignant lesions in the form of a heat map. True positive detections of malignant lesions in detections **114** may be further evaluated by PI-RADS (prostate imaging-reporting and data system) scoring model **116** to generate findings **118** to assess the true positive malignant lesions identified in detections **114** with a score from PI-RADS 1 to PI-RADS 5 indicating the likelihood of clinically significant cancer.

[0018] Advantageously, the embodiments described herein supplement the candidate malignant lesion detection stage with the false positive reduction stage, whereby false positive reduction model **112** classifies the candidate malignant lesions identified in detections **106** of detection model **104** as true positive detections or false positive detections of malignant lesions. Accordingly, false positive reduction stage reduces false positive detections of malignant lesions of detection model **104** with minimal impact on sensitivity provided by detection model **104**, thereby reducing unnecessary and invasive inventions on the patient and decreasing medical costs.

[0019] FIG. **2** shows a method **200** for reducing false positive detections of malignant lesions, in accordance with one or more embodiments. Method **200** will be described with continued reference to workflow **100** of FIG. **1** where steps **202** and **204** of FIG. **2** correspond to candidate malignant lesion detection stage **120** of FIG. **1** and steps **206**, **208**, and **210** of FIG. **2** correspond to false positive reduction stage **122** of FIG. **2**. In one embodiment, method **200** is performed by any suitable computing device or devices, such as, e.g., computer **602** of FIG. **6**.

[0020] At step **202**, one or more input medical images of a patient are received. The input medical images may include images depicting lesions or other abnormalities (e.g., nodules) that may or may not be malignant. In one embodiment, the input medical images may be mpMRI slices. An mpMRI image combines a number (e.g., 8 or more) of individual images acquired under different imaging protocols. For example, the input medical images may be mpMRI images **102** of FIG. **1**. However, it should be understood that the input medical images may be of any suitable modality, such as, e.g., x-ray, magnetic resonance imaging (MRI), ultrasound (US), computed tomography (CT), single-photon emission computed tomography (SPECT), positron emission tomography (PET), or any other suitable modality or combination of modalities. The input medical images may be of any suitable dimensionality, such as, e.g., two dimensional (2D), 2.5 dimensional (2.5D), or three dimensional (3D). The input medical images may be received directly from an image acquisition device, such as, e.g., image acquisition device **614** of FIG. **6**, used to acquire the input medical images. Alternatively, the input medical images may be received by loading medical images previously stored on a memory or storage of a computer system (e.g., a picture archiving and communication system, PACS) or by receiving the input medical image data via network transmission from a remote computer system. In some embodiments, the input medical images may be patches extracted from a medical image.

[0021] At step **204**, a candidate malignant lesion is detected from the one or more input medical images. The candidate malignant lesion is a “candidate” in that, while the lesion is detected as being malignant, the detected malignant lesion may be a false positive detection of a malignant lesion. The candidate malignant lesion may be detected using any suitable approach. For example, the candidate malignant lesion may be manually detected by a user (e.g., radiologist) or may be automatically or semi-automatically detected. Once detected, the candidate malignant lesion may be identified in any suitable manner, such as, e.g., in a heat map or a binary mask. In one embodiment, the candidate malignant lesion is detected using detection model **104** of FIG. **1** and identified in detections **106** in the form of a heat map.

[0022] In one embodiment, the candidate malignant lesions are automatically detected using a trained machine learning based detection network. The detection network in this embodiment comprises a UNet architecture with 2D residual blocks including 5 down sampling blocks and 5 up sampling blocks. Each residual block is implemented with a bottleneck architecture with a stack of 3 layers. The first residual block includes 16 filters, with doubling filter sizes for each remaining block.

[0023] At step **206**, one or more patches associated with the candidate malignant lesion are extracted from the one or more input medical images. The patches are images depicting at least a portion of the input medical images. The patches may be extracted from the input medical images by, e.g., cropping the input medical images. The patches may be of any suitable (e.g., predetermined) dimension or dimensions. In one embodiment, the patches are patches **110** extracted from mpMRI images **102** of FIG. **1**.

[0024] In one embodiment, the patches associated with the candidate malignant lesion include a patch depicting the candidate malignant lesion centered around a center of the candidate malignant lesion. For example, the patch depicting the candidate malignant lesion may be extracted from a 2D mpMRI slice I_S and centered around a center of the candidate malignant lesion. In one embodiment, the patches associated with the candidate malignant lesion also include patches from medical images neighboring the medical image depicting the candidate malignant lesion for contextual information. For example, the patches associated with the candidate malignant lesion may include a patch extracted from the 2D mpMRI slice I_S, as well as patches extracted from neighboring adjacent 2D mpMRI slices I_{S+1}, I_{S-1}. The patches extracted from the neighboring mpMRI slices I_{S+1}, I_{S-1} are extracted at a location corresponding to (i.e., at a same relative location to) the location that the patch depicting the candidate malignant lesion was extracted from the mpMRI slice I_S. The patch extracted from 2D slice I_S and the